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Role Allocation in Human-Robot Interaction Schemes for Mission Scenario Execution

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Abstract **- In this paper, we focus on the problem of maximizing system performance for future space exploration missions involving both human and robot agents. One of the main challenges in human-robot interaction scenarios is determining which tasks are best done with either human, robotic systems, or in collaboration with each. Such partitioning of the task space must acknowledge the capabilities of both agents, as well as incorporate the effect of repetitive workload, or stress, on the human operator. Our methodology for role allocation, which typically consists of either the human or the machine executing a single task, is based on predicting system performance of a given scenario by incorporating the concept of task switching. Task switching is defined as the process of alternating or switching attention between tasks when responding to a sequence of stimulus presentations. Using this concept, system performance can be predicted and used to determine an optimal allocation of tasks to be divided between human controlled and autonomous robotic systems to minimize mental workload while maximizing task performance. We provide details of the approach in this paper and present our results as applied to a simulated rendezvous/docking mission scenario.**

Index Terms – Human-Robot Interaction, Task Allocation, Space Exploration, Performance Assessment

I. INTRODUCTION

As human-robotic systems are increasingly deployed in future space exploration scenarios, such as Moon exploration, in-space assembly operations, and habitat construction [1], there is a corresponding need to develop methods that optimally partition the task space to ensure mission success. In this paper, we focus on the problem of maximizing system performance for future space exploration missions by acknowledging the capabilities of both agents, as well as incorporating the effect of repetitive workload, or stress, on the human operator. In our approach, partitioning the task space involves predicting system performance of a given mission scenario by constructing an optimization function based on the concept of task switching. This involves analyzing the effect of task switching, i.e. the cost associated with switching attention between two tasks, in two different dimensions – task switching within a scenario, and task switching between iterations of the same scenario. This predicted system performance parameter can then be used to determine an optimal allocation of tasks to be divided between human and robotic-system to minimize mental workload while maximizing task performance.

II. BACKGROUND

The first formal research in role allocation for human-machine scenarios is addressed in [2], in which decisions between machine versus human control are made based on a simple comparison of capabilities. Earlier work in role allocation is also found in [3] in which human and machine capabilities are scaled in order to determine when role transitions should occur. Olsen and Goodrich [4] develop a model to allocate roles in human-robot interaction schemes based on assessment of the number of robots a single individual can control in a given scenario. In [5], a human-centered approach is used to understand the role of human-robotic teamwork in future human space exploration missions. In this work, a framework is developed in which robots become functional tools that assist the human rather than replace the human operator. In [6, 7], the focus is to change roles by dynamically adjusting the autonomy of an intelligent agent based on human physiological responses [6] and reasoning about the costs of decisions [7]. Role allocation in human and robot teams is proposed in [8,9] using an analytical framework that decomposes tasks into independent functional primitives. In [10], Sheridan presents a ten level autonomy scale that allows for intermediate collaboration between human and machine and complementary research is presented in [11] that introduces taxonomies and metrics for task-oriented human-robot interaction in terms of five task categories dependent on the level of human interaction.

Previous research in human-robot role allocation typically looks at the capabilities of the human and robot agent based on expected performance. Although research in human-robot task allocation is expanding, an approach that integrates the expected contributions of both human and robot agents to estimate performance has been only limitedly addressed. This work attempts to address these limitations by developing a systematic approach that incorporates the various effects of workload on human performance and predicts system performance derived from allocation of tasks between human-controlled and autonomous robotic systems. The overall objective is to use performance characteristics to determine an optimal allocation of tasks to be divided between human and robotic-system to minimize mental workload while maximizing task performance, as necessary for such future mission scenarios as Mars exploration, habitat construction, and in-space assembly.

III. Role Allocation in Human-Robot Interaction Schemes

The process of role allocation involves estimating a suitable allocation of tasks between humans and machine that maximizes the performance of a system. The first step in this process involves constructing an optimization function that incorporates aspects of the performance associated with individual task execution into estimates of the performance for implementation of a sequence of tasks. This sequence execution parameter (SEP) represents the performance associated with a designated allocation of tasks between humans and machine. To use the sequence execution parameter as a representation of our optimization function, we must analyze different combinations of task operations executed by different agents at different times. This is due to the fact that the sequence execution parameter not only varies due to the agent's performance on individual tasks, but depends, as well, on the sequential relationship between tasks.

The main theory underlying the process for determining the sequence execution parameter is dependent on the concept of task switching [12-14]. Task switching is defined as the process of alternating or switching attention between tasks when responding to a sequence of stimulus presentations. Previous research has shown that the cost of switching increases when a human participant is required to alternate between tasks, but that this switching cost is not significantly dependent on the nature or difficulty of the task. Although the exact value of the switching cost (typically computed as a time factor) depends on differences in the experimental setup, there is general consensus on the different type of factors that affect the cost of switching.

A scenario is defined as a sequence of tasks that are necessary to achieve a desired goal. When determining the sequence execution parameter associated with a scenario, we must analyze two different dimensions – task switching within a scenario, and task switching between iterations of the same scenario. To further clarify our approach, we define some common terminology associated with the task-switching paradigm.

- Switching cost is defined as the difference in performance of an individual task on trial k when participants perform a different task on trial $k-1$.

- The Response-Stimulus Interval (RSI) is defined as the time interval between the completion of a task and the presentation of the next stimuli for implementation of the next task.

- Transition cost is defined as the difference in performance of a task sequence (i.e. scenario) on trial n when participants perform a different task sequence on trial $n-1$.

- Task inertia, which reduces task-to-task switching cost, develops when a sequence of tasks belonging to the same scenario are repeatedly performed.

Based on these common definitions, our sequence execution parameter can be determined based on augmenting the summation of individual task performance values with derived values from the four parameters. To determine these values, we further analyze the task-switching results from the human participant studies performed in [12-14], to derive the following observations related to our application:

- Observation 1
  - By increasing the response stimulus interval (RSI), the switching cost decreases accordingly. Based on analysis of the relationship between switching cost and RSI, the switching cost associated with short RSI (20ms), is larger than with longer RSIs (550 ms), with no further reduction in switching cost after 1100ms.

- Observation 2
  - Transition costs are highest at the first introduction of a new sequence.

- Observation 3
  - By increasing task inertia (i.e. increasing the number of times a sequence of tasks is repeated), transitioning to a different task sequence results in higher transition costs.

- Observation 4
  - Increasing task inertia decreases transition costs between task sequences.

The parameters associated with the task-switching paradigm are typically noisy, as they are computed based on human participation data extracted from averaging the results of many experiments and based on a diverse set of users. As such, we evaluate the sequence execution parameter using a fuzzy logic construct.

Fuzzy logic [15] is a superset of Boolean logic that has been extended to deal with the notion of partial truths in which truth values range from [0.0, 1.0], where 0.0 represents absolute Falseness and 1.0 represents absolute Truth. With this construct, membership values (i.e. truth values) are used to represent the degree to which an input or output value belongs to a variable, represented symbolically by a fuzzy set. Determination of membership values is accomplished through the utilization of a set of if-then rules that relate inputs to system outputs. These linguistic fuzzy sets and conditional statements allow us to model switching and transition costs based on information extracted from the noisy, imprecise, experimental data derived from the human participants.

For our purposes, we categorize switching and transition costs into the linguistic fuzzy set {Zero, VerySmall, Small, Medium, Large, VeryLarge}, which is defined based on the membership functions as depicted in Figure 1.

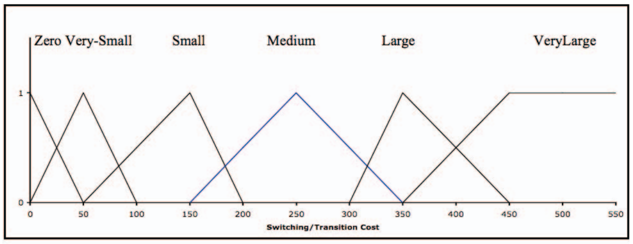

Figure 1. Fuzzy membership functions depicting switching and transition costs

A. Observation 1: Fuzzy Rule Set (f_{obs1})

Figure 2a depicts the relationship between the response stimulus interval RSI and human response time as defined in [13]. We represent RSI by the linguistic fuzzy set {SHORT, LONG} as depicted in Figure 2b. Based on Figure 2a, we determine the effect of RSI on the switching costs associated with transitioning from task *k* to a different task at *k-1*. We model this relationship based on the following fuzzy rule set:

- If RSI is SHORT then SwitchingCost is MEDIUM
- If RSI is LONG then SwitchingCost is SMALL

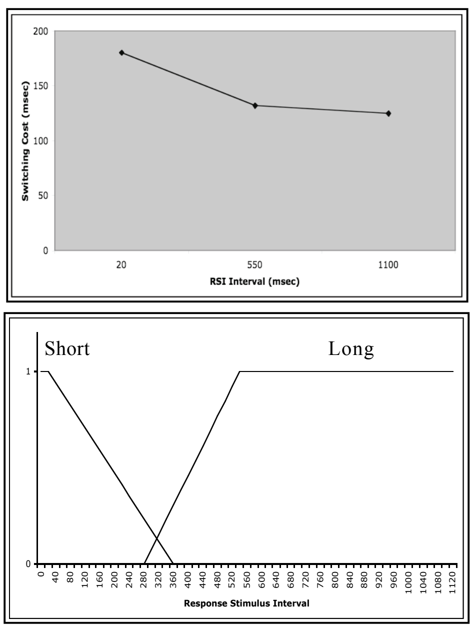

Figure 2: a) Depicts Response Stimulus Interval with respect to Switching Cost b) Membership functions representing RSI

Figure 3 depicts the relationship between task inertia and human response time as discussed in [12], where we represent task inertia by the linguistic fuzzy set {SMALL, MEDIUM, LARGE, VERYLARGE}. Based on human participation data [12], we construct rule sets that incorporate Observations 2, 3, and 4 as discussed below.

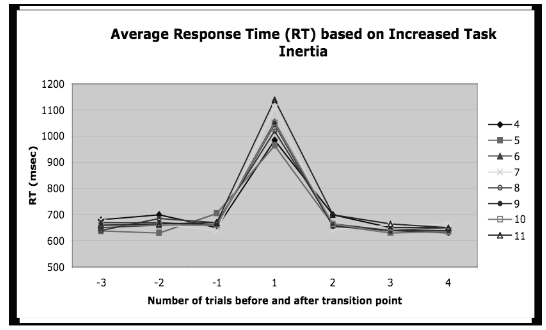

Figure 3. Depicts average response time for the three trials before and four trials after the transition point. The separate curves represent changes in the transition point, which occurs after trials 4 through 11, and corresponds to increased task inertia.

B. Observation 2: Fuzzy Rule Set (f_{obs2})

From Figure 3, we calculate that the maximum transition cost associated with the initial task sequence is associated with the VERYLARGE membership value. This gives us an initialization value for transition cost, such that:

$$\text{TransitionCost}_0 = \text{VERYLARGE}$$

C. Observation 3: Fuzzy Rule Set (f_{obs3})

Based on Figure 3, we determine the effect increasing task inertia has on the transition costs associated with transitioning to a different task sequence. Transition costs, depicted in Figure 4, are computed as the difference in average response time for the three trials before the transition point, and the response time of the first trial after the transition.

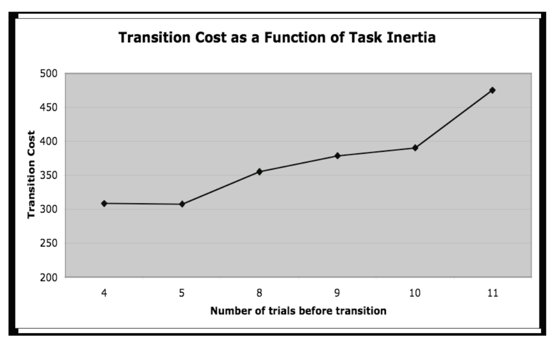

Figure 4. Graph associating transition cost and task inertia before the transition point

This relationship, associated with Observation 3, is used to derive the following rule-set:

- If Transition is TRUE
  - If Task-Inertia is SMALL OR Task-Inertia is MEDIUM then TransitionCost is MEDIUM

- o If Task-Inertia is LARGE then TransitionCost is LARGE
- o If Task-Inertia is VERYLARGE then TransitionCost is VERYLARGE

D. Observation 4: Fuzzy Rule Set (f_{obs4})

Based on Figure 3, we determine the effect increasing task inertia has on the transition costs associated with repetition of the same task sequence. Transition costs are computed as the difference in average response time between trial *n* and trial *n-1* after the transition and is depicted in Figure 5.

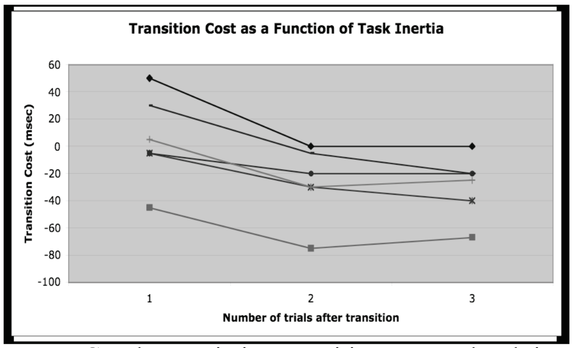

Figure 5. Graph associating transition cost and task inertia after the transition point

From Figure 5, we model the transition cost associated with Observation 4 based on the following rule-set:

- If Transition is FALSE
  - o If Task-Inertia is SMALL then TransitionCost is VERYSMALL
  - o If Task-Inertia is NOT SMALL then TransitionCost is ZERO

The four observations provide us with four rule sets. By combining the outputs from these rules, we can determine the sequence execution parameter associated with a given scenario using the algorithmic approach discussed in the next section.

IV. Algorithmic Approach for Predicting System Performance

The sequence execution parameter (SEP) is used to predict performance associated with a designated allocation of tasks between humans and machine. The following algorithm outlines our methodology for calculating the sequence execution parameter:

A. Compute the current task allocation vector for each agent, such that:

$$t_n^r = \begin{bmatrix} r_1^n & r_2^n & \dots & r_k^n \end{bmatrix}$$
$$t_n^h = 1 - t_n^r$$

where the variables are defined as:

n: the current scenario run
k: number of tasks in scenario n
t_n^r: robot task vector
t_n^h: human task vector
$r_j^n = 1$: if robot agent performs task *j* in scenario *n*
$r_j^n = 0$: if human agent performs task *j* in scenario *n*

B. Determine switching cost s_j for task $j \in (1,k)$ in current scenario n

if $r_j^n = 1$ then $s_j = 0$
else
a. Determine response stimulus interval RSI between current human task and last human task
if *j = 1*, $RSI_j = 1100$
else $RSI_j = (\rho_{j-1} \times r_{j-1}^n) + \sum_{i=1}^{j-2} (\rho_i \times r_i^n) r_{i+1}^n$

b. Calculate Switching Cost associated with RSI
$s_j = f_{obs1}(RSI_j)$

where the variables are defined as:
p_j: value associated with agent performance of task j

C. Determine transition cost τ for task $j \in (1,k)$ in current scenario n

if *n=1*
Task inertia value: $\mu = 0$
$\tau_j = f_{obs2}(TransitionCost_0)$
else
if $t_{n-1}^h = t_n^h$:
Increment task inertia value: $\mu = \mu + 1$
$\tau_j = f_{obs4}(\mu)$
else
$\tau_j = f_{obs3}(\mu)$
Task Inertia Value: $\mu = 0$

D. Calculate the sequence execution parameter by incorporating switching and transition cost in the task performance computation as defined in [9].

$$SEP_n = \begin{bmatrix}\rho_1^r & \rho_2^r & \dots & \rho_k^r\end{bmatrix} t_n^r + \begin{bmatrix}(\rho_1^h + s_1 + \tau_1) - \nu_{n,1}^h & \dots & (\rho_k^r + s_k + \tau_k) - \nu_{n,k}^h\end{bmatrix} t_n^h$$

where the variables are defined as:

s_j : switching cost for task $j \in (1,k)$

τ_j : transition cost for task $j \in (1,k)$

ρ_j : performance value for completing task $j \in (1,k)$

$\nu_{n,j}^h$: human workload value associated with completing task j in scenario n

This algorithmic model functions as our optimization function to determine performance associated with the allocation of tasks between humans and machine. We must now extract the maximum of our optimization function to estimate a suitable task allocation scheme. We employ genetic algorithms to search the space of allocation possibilities.

V. Human-Robot Task Allocation Search

Genetic algorithms [16] are a methodology for searching through the space of solution possibilities using the concept of evolution. By constructing individual chromosomes that consist of possible solutions in the search space, genetic algorithms determine the fitness of an individual based on an objective function. In this application, our chromosomes are coded based on the task allocation vector. Our sequence execution parameter functions as our objective function. The genetic algorithm process consists of the following steps:

- Create initial population
  - Select random allocations as possible solutions to the human-robot task allocation scenario.
- Evaluate fitness
  - Compute the sequence execution parameter for each task allocation vector in the population.
- Reproduce
  - Select vectors with the highest fitness value and reproduce offspring for next generation.
- Create next generation
  - If new generation contains optimal solution, select vector as the desired human-robot task allocation vector, else continue through evolution process.

Based on employing genetic algorithms with our sequence execution parameter functioning as our optimization function, we now compare results from our task allocation scheme against a scheme that only incorporates individual task performance metrics.

VI. Test Results

HumAnS-3D (Figure 6) is a 3D virtual test environment developed to allow user access to a virtual representation of the world and control of a virtual robot. The control panel allows the human operator to command the robot to move forward, backward, and turn either left or right. The graphical user interface also connects the virtual robot, viewable by the human user, to the real robot for seamless integration with the real world environment. For our application, we utilize the Sony ERS-7 robot for interaction.

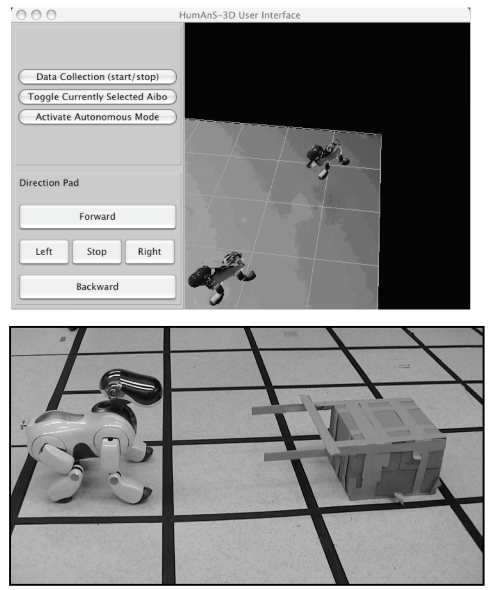

Figure 6. Virtual environment consisting of human operator unit and 3D World Environment

It is envisioned that future planetary exploration missions will involve humans and robots working in collaboration to accomplish both scientific and exploration goals [17]. For assessment of our methodology, we apply our approach to a simulated rendezvous/docking task, applicable to enabling this vision, and determine a suitable allocation of tasks. The primary roles for this mission scenario are depicted in Figure 7, with the corresponding performance metrics documented in Table I. In Table I, the *Sequence Designation* parameter designates the sequential relationship between tasks. Further details on the process of task decomposition for this scenario can be found in [9].

Figure 8 depicts the graphs comparing the role allocation methodology with allocation results from a fitness function that only incorporates individual task performance values (i.e. it is not based on the sequence execution parameter). We note that, by incorporating the sequence execution parameter into the fitness function, the role transition from human controlled to autonomous robot typically occurs earlier in the sequence cycle. For implementation of the first task, each role allocation methodology provides equivalent results.

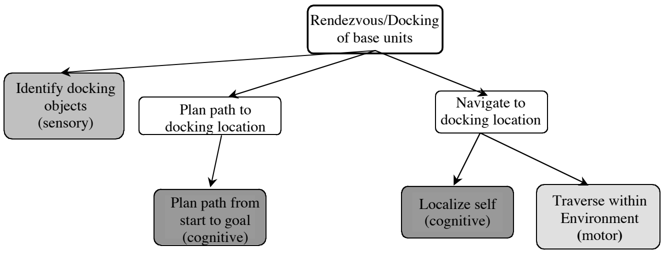

Figure 7. Role decomposition for simplified rendezvous/docking scenario

Table I. Performance metrics associated with simplified scenario decomposition

Workload Value (0-10)	Performance Score (0-10)		Task Primitives	Sequence Designation
	Human	Robot		
			Motor Activity	
4.0	9.6	5.0	Traverse within environment	Task 4
			Cognitive Activity	
9.0	5.0	2.0	Localize with respect to environment	Task 3
10.0	4.1	3.5	Plan path within environment	Task 2
			Sensory Activity	
3.0	7.9	7.0	Identify objects within environment	Task 1

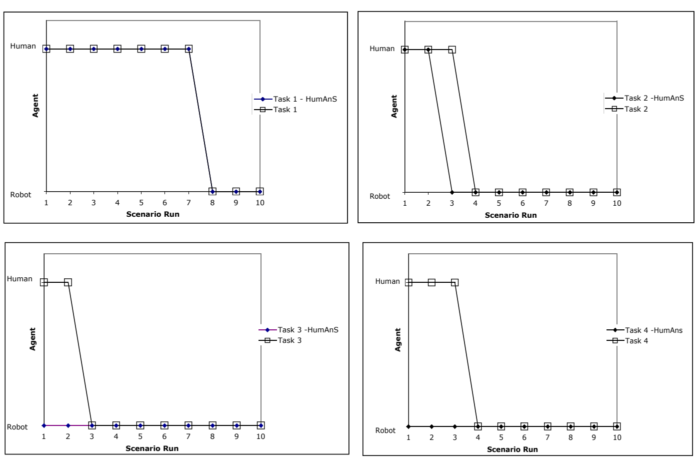

Figure 8. Graphs comparing role allocation results of Task 1-4 for repetitive scenario runs

Table II: Schemes to compare results from role allocation methods

	Task Allocation Scheme							
	Task 1		Task 2		Task 3		Task 4	
Scenario Run	Human	Robot	Human	Robot	Human	Robot	Human	Robot
1	X		X		X		X	
1 – HumAnS	X		X			X		X
2	X		X		X		X	
2 - HumAnS	X			X		X		X
8		X		X		X		X
8 - HumAnS		X		X		X		X

To validate the allocation methodology with real-world implementation data, we ran through the rendezvous/docking scenario using HumAnS-3D with six different allocation schemes (of human controlled versus autonomous robot) as shown in Table II and compared their execution times as shown in Figure 9. These scenarios correspond to the role allocations associated with Scenario Run 1, Scenario Run 2, and Scenario Run 8, as depicted in Figure 8. We note that, in some cases, the allocation schemes derived are the same.

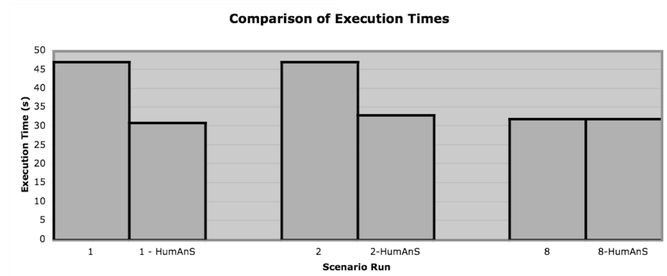

Figure 9. Comparison of methodologies for scenario runs

According to the real-world implementation data, the role allocation computed by our methodology results in faster real-world execution than the traditional method. These results provide preliminary validation of our allocation methodology.

VII. Conclusions

In this paper, we present a methodology that predicts system performance for determining an optimal allocation of tasks to be divided between human controlled and autonomous robotic systems. The goal of the method is to minimize mental workload while maximizing task performance as necessary for achievement of human-robot interaction scenarios. We have discussed our methodology in detail and compared its implementation on a representative rendezvous/docking mission scenario. The implementation of the method is shown to provide a correlated comparison that maximizes the actual performance of human-robotic systems operating in the real world. Future work will focus on tasks that require collaboration between humans and robots such that tasks must be implemented concurrently to achieve success.

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